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IMPLEMENTATION OF ARIMA MODELS ON DEMAND FORECASTING AT PT WORLD YAMATEX SPINNING MILLS

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Abstract
Company activities are in uncertain circumtances so need for tool or method to predict or forecast the future is deeply needed. This research, forecasting method, uses Autoregressive Integrated Moving Average (ARIMA). ARIMA have ability to solve the forecasting problem by applying Autocorrelation And Partial Autocorrelation Coefficients. Temporary model are (2,2,1)(1,1,1)$_{15}$, (1,1,2)(1,1,1)$_{15}$, and (2,1,2)(1,1,1)$_{15}$. Checking for Ljung-Box Q Statistics by Chi-Square (X^2), one of the result are p-value at lag 12 is 0.01, 0.039, and 0.024 for each model, because the closest value to 0.05, so the chosen model is ARIMA(1,1,2)(1,1,1)$_{15}$
Keywords: Autoregressive Integrated Moving Average, Autocorrelation And Partial Autocorrelation Coefficients, Model Analysis.

1. INTRODUCTION

PT *World Yamatex Spinning Mills* is manufacture which is making 100% combed cotton yarn. Addresess in Padasuka 47A, Bandung. Because the manufacture have to produce yarn routine (make to stock) and special order (make to order). Here why, the manufacture need forecasting demand.

The manufacture have many problem in production and planning inventory control division, one of them are determine exact number cotton yarn to produced each month so the demand forecast for yarn type such PM and CM. This efforts for anticipate uncertain sum of demand in near future.

2. Autoregressive Integrated Moving Average (ARIMA)

2.1 Autoregressive Integrated Moving Average (ARIMA)

ARIMA methodology is different from most methods because it does not assume any particular pattern in the historical data of the series to be forecast. It uses an iterative approach of identifying a possible model form a general class of models. The chosen model is the checked against the historical data to see whether it accurately describes the series. This itterative procedure continues until a satisfactory model is found.

In *time series* analysis, there is fundamental distinction between the terms ”process” and ”realization”. The actual values in an observed time series are the realization of some underlying process that generated those values.

The purpose of time series analysis is to use the realization of process to identify a model of the ARIMA process that generated the series. ARIMA model building is an empirically driven methodology of systematically identifying, estimating, diagnosing, and forecasting time series. The purpose of ARIMA analysis is to find a model that accurately represents the past and future patterns of a time series.

$$Y_t = Pattern + e_t$$

2.2.1 Four Steps Of ARIMA Model Building

1. Model identification
   Using graphs, statistics, ACFs, PACFs, transformtions, etc., achieve stationarity and tentaviely identify patterns and model components.
2. Parameter Estimation
   Determine model coefficients through sofware applications of least squares and maximum likelihood methods.
3. Model Diagnostics
   Using graphs, statistics, ACFs, PACFs of residual, determine if the model is valid. If valid, use the model, otherwise repeat identification, estimation, diagnostic steps..
4. Forecast Verification And Reasonableness
   Using graphs, simple statistics, and confidence intervals determine the

validity of forecasts and track model performance to detect out of control situations.

In ARIMA terms, a time series is a linear function of past actual values and random shocks (error terms)

$$Y_t = f[Y_{t-k}, e_{t-k}] + e_t \quad , \quad k > 0$$

Our purpose is to extract all possible information from a time series so that e_t's are distributed as white noise.

The objective of ARIMA analysis is to design the right pattern empirically, we do not choose a forecasting model a priori before analysis begins. Confirmation that the correct pattern has been identified requires meeting several diagnostic characteristics, including moedl residual (e_t's) distributed as white noises.

By definition, white noise is normally and independently distributed (NID), having no pattern, a zero mean,and a error variance that is lower the variance of Y_t.

2.2.2 ARIMA Notation(p, d, q)

ARIMA model building methods use a simple, versatile model notation, they are designated by the level of autoregression, integration, and moving averages. This standard notation identifies the orders of autoregression by *p*, integration or differencing by *d*, and moving averages by *q*.

1. *Autoregressive Process – ARIMA(1,0,0)*

$$Y_t = \theta_0 + \phi_1 Y_{t-1} + e_t$$

θ_0 and ϕ_1 are coefficients chosen to minimize the sum of squared. For an ARIMA(1,0,0) model, the absolute value of coefficient ϕ_1 is normally constrained to be less then 1.

$$|\phi_1| < 1$$

2. *Moving Average Process – ARIMA(0,0,1)*

$$Y_t - \mu = -\theta_1 e_{t-1} + e_t$$
$$Y_t = \mu - \theta_1 e_{t-1} + e_t$$

This model are similiar to exponential smoothing. θ_1 is an estimated coefficient and Y_t is only correlated with the previous forecast error, e_{t-1}.

$$|\theta_1| < 1$$

3. *Integrated Process – ARIMA(0,1,0)*

The patterns in time series are the result of fundamental processes. A deterministic trend is a systematic period-to-period increase od decrease that persists for many time periods. Becasue trends represent important long-run general movemants in a time series, they are important to model.

Integrated processes are level-nonstationary series. Trends and random walks are level-nonstationary because their means are not constant. The means either randomly change as the series randomly walks or consistently increases (decrease). A random walk behavior (drift) is called a stochastic trend, while a consistent period-period change is called a deterministic trend

If a series is a random walk, then the previous actual is a best predictor of all future values.

$$\ddot{Y}_t = Y_{t-1}$$
$$\ddot{Y}_t = Y_{t-1} + e_t$$

4. *Deterministic Trend Process – ARIMA(0,1,0)1*

Is an example of an integrated component of an ARIMA model, the second "1" of the notation ARIMA(0,1,0)1 is used when *d* > 0.

$$\ddot{Y}_t = Y_{t-1} + \theta_0$$
$$Y_t = Y_{t-1} + \theta_0 + e_t$$

θ_0 is an parameter equal to the mean of the period-period changes (trend).

$$\ddot{Y}_{t+m} = Y_t + m\theta_0$$

t is the period of the last actual and m is the forecast horizon.

Several of the tools used to identify ARIMA models should be familiar to you:

1. *Autocorrelations Functions ACF(k)s.*
2. *Partial Autocorrelations Functions PACF(k)s.*
3. Series graph and plots.
4. Descriptive statistics.

3. Research Method

3.1 Model Identification

PT WYSM have two tipe master yarn production are CM and PM. Second is calculate *total demand* with sum CM and PM. (at the table1.1)

The term of ARIMA method is n, must or more than 72 period. Because PT WYSM only can supply for 28 period, then we

must shape the rest with help ARENA10.0 software for 72 period left (table 4.3).
For Determine the plots of ACFs and PACFs using MINITAB15.0 software, Figure 1.4 and 1.5 show stationarity condition values between 0,2 until -0,2 and have trend so need to be *differencing*, then temporary model is ARIMA(1,1,1).
We see in results MINITAB15.0, values of ACF at lag 15 is 0.15518, lag 33 is 0.156055, and lag 50 is 0.14103 have similiar values, so we conclude that the series have seasonal pattern each and every 15 period. So the model now si ARIMA(1,1,1) $(1,1,1)_{15.}$

3.2 Parameter Estimation
The next step is building parameter with help MINITAB15.0 software, *trial and error* the model until the paramater found. (table 1.4)

3.3 Diagnosa
If the *p*-value associated with the *Q* statistic is small (say, *p*-value > 0.05), the model is considered adequate.

3.4 Peramalan
The results of forecasting can be seen in figure1.7 .

4. Conclusion
The demand series showing the stationarity still inside maximum and minimum boundary, but not showing the values of AFCs and PACFs is drop, so need to *differencing*..
Other analysis can be determine by the minimum deviation at Period 101 in ARIMA(1,1,2)$(1,1,1)_{15}$ model is 1125727.
The chosen model for forecasting demand problem on PT WYSM is ARIMA(1,1,2)$(1,1,1)_{15}$ model.

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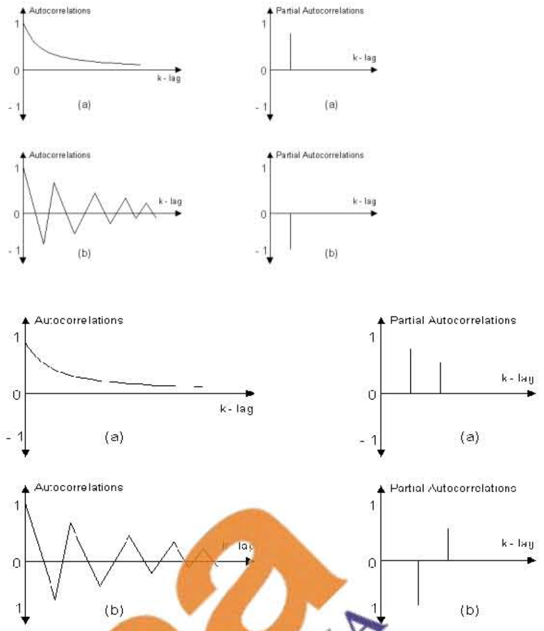

Figure 1.1 ACF dan PACF with notation AR(1) dan AR(2)

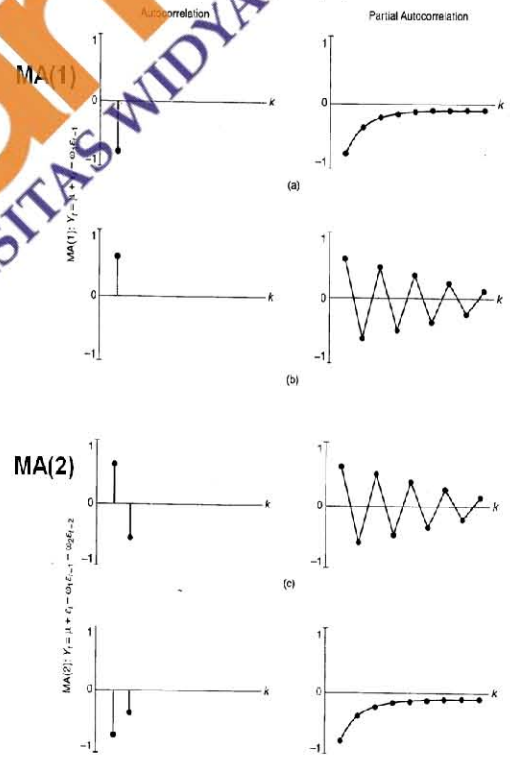

Figure 1.2 ACF dan PACF dengan Notasi MA(1) dan MA(2)

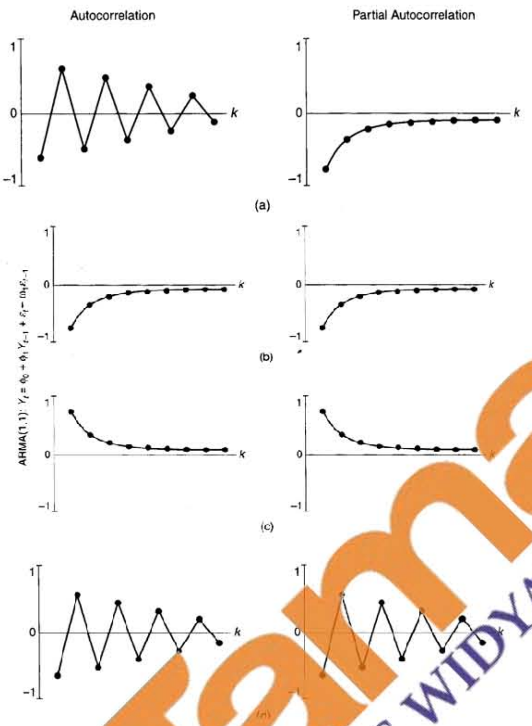

Figure 1.3 ACF dan PACF dengan Notasi ARIMA(1,1)

Tabel 1.1 Total Demand

Periode		Permintaan		Total Demand
Tahun	Bulan	CM	PM	
2007	January	611060	709101	1320161
	Februari	334140	681149	1015289
	Maret	605414	617025	1222439
	April	935908	471605	1407513
	Mei	1028710	352480	1381190
	Juni	857720	566431	1424151
	Juli	966625	782026	1748651
	Agustus	662500	385080	1047580
	September	818440	609940	1428380
	Oktober	435230	431000	866230
	November	860000	418320	1278320
	Desember	682856	177750	860606
2008	January	749300	769760	1519060
	Februari	630000	761010	1391010
	Maret	451060	807630	1258690
	April	474280	420510	894790
	Mei	380920	618000	998920
	Juni	962310	510250	1472560
	Juli	362320	642370	1004690
	Agustus	413280	571280	984560
	September	966057	560375	1526432

	Oktober	661783	635190	1296973
	November	539150	490460	1029610
	Desember	1300650	269670	1570320
2009	January	524360	280610	804970
	Februari	1114560	158900	1273460
	Maret	1147030	285800	1432830
	April	816500	150200	966700

Table 1.2 Demand period Januari 2001 Until Februari 2005

No	Permintaan	No	Permintaan	No	Permintaan	No	Permintaan	No	Permintaan
1	944858	11	1147380	21	1103230	31	1615850	41	876138
2	1491310	12	902031	22	949595	32	1206850	42	1234600
3	889559	13	1407610	23	991312	33	1012180	43	1357930
4	1100880	14	1137580	24	1238830	34	855331	44	1247330
5	880548	15	1172890	25	1456740	35	1257650	45	1273870
6	962794	16	1361690	26	1674730	36	831814	46	1613510
7	1355200	17	844026	27	1628160	37	1614790	47	1145930
8	1585000	18	1243200	28	1676160	38	1454600	48	1175700
9	1526570	19	1530180	29	1630330	39	877446	49	1107330
10	1142640	20	1077130	30	895372	40	1104120	50	908989

Table 1.3 Permintaan period Maret 2005 Until April 2009

No	Permintaan	No	Permintaan	No	Permintaan	No	Permintaan	No	Permintaan
51	1317590	61	1378450	71	1164250	81	1428380	91	1004690
52	1441710	62	1181890	72	1509830	82	866230	92	984560
53	1281640	63	1335050	73	1320161	83	1278320	93	1526432
54	1133010	64	1499440	74	1015289	84	860606	94	1296973
55	1217950	65	1144240	75	1222439	85	1519060	95	1029610
56	1255560	66	890129	76	1407513	86	1391010	96	1570320
57	1477270	67	1025960	77	1381190	87	1258690	97	804970
58	1450530	68	1548460	78	1424151	88	894790	98	1273460
59	941117	69	882385	79	1748651	89	998920	99	1432830
60	1288030	70	1247930	80	1047580	90	1472560	100	966700

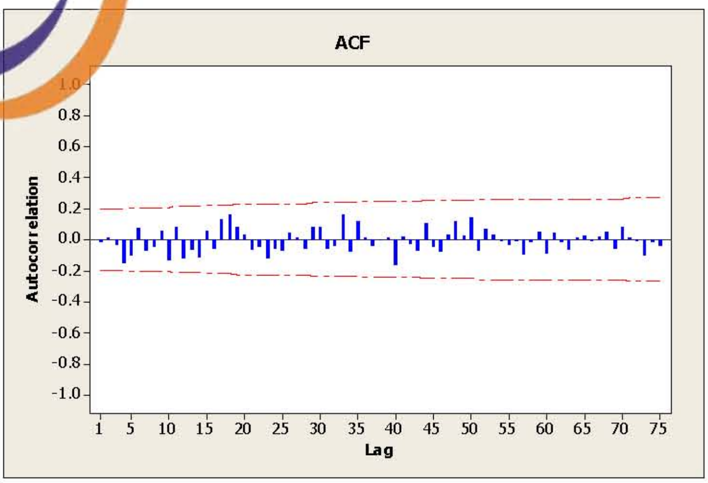

Figure 1.4 *Autocorrelation Function*

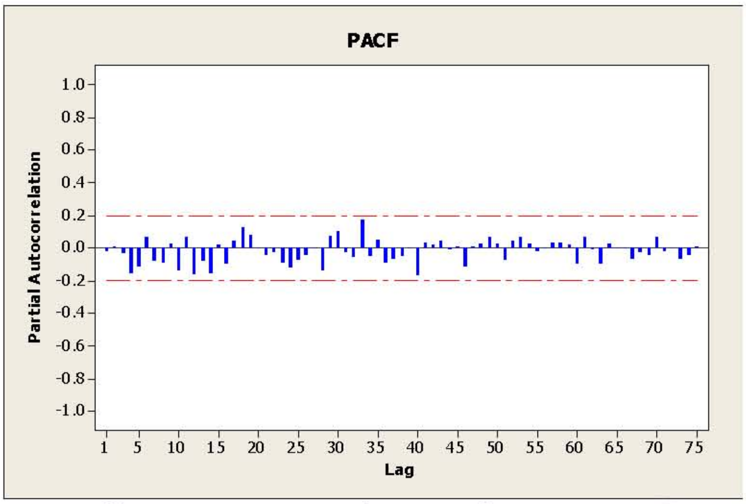

Figure 1.5 *Form Partial Autocorrelation Function*

Table 1.4 Trial And Error Model ARIMA

Model ARIMA	Jumlah Iterasi	Keterangan
(1,1,1)(1,1,1)	17	Tak Terdefinisi
(2,1,1)(1,1,1)	15	Tak Terdefinisi
(2,2,1)(1,1,1)	25	Terdefinisi
(2,2,2)(1,1,1)	25	Tak Terdefinisi
(1,2,2)(1,1,1)	25	Tak Terdefinisi
(1,1,2)(1,1,1)	25	Terdefinisi
(1,2,1)(1,1,1)	18	Tak Terdefinisi
(2,1,2)(1,1,1)	25	Terdefinisi

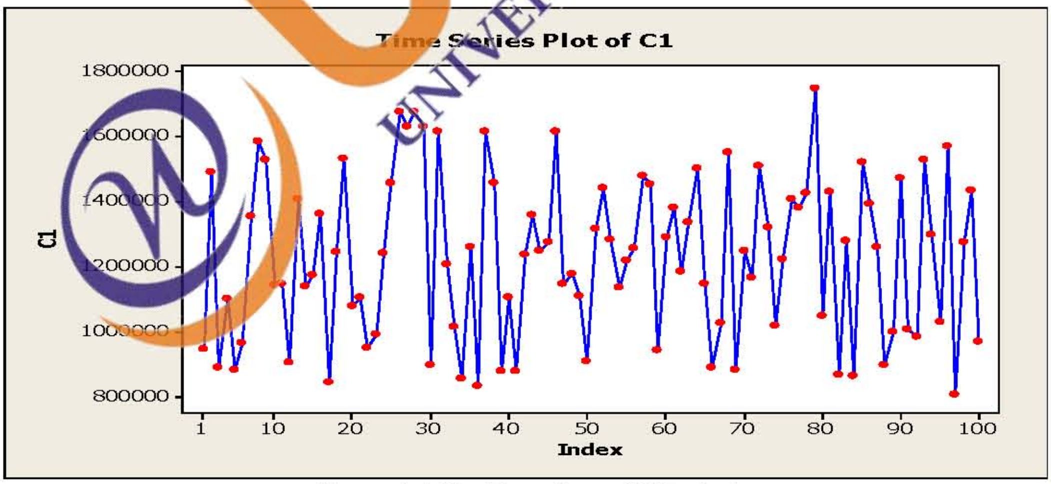

Figure 1.6 *Plot Time Series* 100 Period

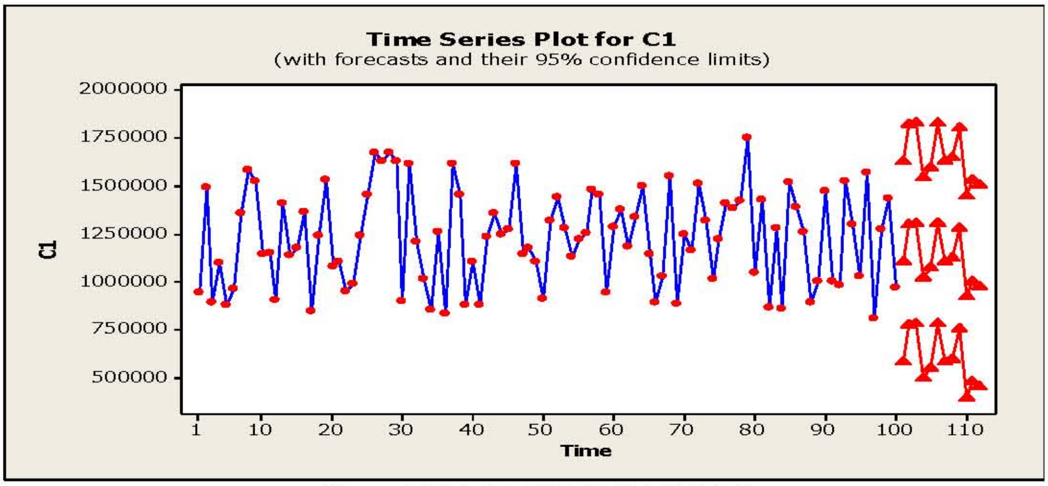

Figure 1.7 Model ARIMA $(1,1,2)(1,1,1)_{15}$